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Analysis of Pedestrian Accidents Using Structural Equation Model

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Abstract

A structural equation model (SEM) is adopted to capture the complex relationships between different factors because the model can handle such relationships between endogenous and exogenous variables simultaneously and it can also associate latent variables in the model. In this study, we used accident data having 704 pedestrian accident recorded in Vadodara city since 2013 to 2017 and estimated relationship among exogenous factors and traffic accident size. The model suggests that road factors, vehicle factors, victim factors and time factors are strongly related to the accident size. In this study, structural equation modeling was applied to estimate the accident size based on accident data of Vadodara city. By considering total ten observed variables and four latent variables. The regression weights were obtained by solving equation. In a conflict between vehicle and pedestrian, the injuries due to motorised two-wheeler (M2W), car and three-wheeler attributing to high regression weights in the model. In conjunction to this, from the model it was inferred that fatalities among the victims dominated due to Light Commercial Vehicle (LCV) and Heavy Commercial Vehicle (HCV). Among three exogenous latent variables (road, vehicle and time factors), the effect of vehicle factor on accident size is highest. In order to decrease the traffic accident size handling the road factor is more effective than handling vehicle and time factors. It can be a positive result to traffic engineers because as they can handle 'road factors', they hardly manage 'vehicle and time factors'. The findings in this research offer information about the relationships between accident size and various factors and they can contribute to reduce traffic accident size. Although there are countless factors having relation to "accident size", obtainable information from fields is very limited. Hence, some aspects may not be properly described and explained by models.

Keywords: Pedestrian Accident; Accident Size Analysis; Factor Analysis; Structural Equation Modeling.

Introduction

Traffic accident forecasting models have been developed to understand factors affecting traffic accidents and eventually to reduce traffic accidents by controlling and/or improve factors. There are ample studies have been done on road accident analysis using traditional methods like Generalized Equation Modeling (GLM). Accident statistics most often used to quantify and describe three principal informational elements: accident occurrence, accident involvements and accident severity. Accident occurrence relates to the numbers and types of accidents, accident involvements concerns the numbers and types of vehicles and drivers involved in accidents, and accident severity is generally expressed as the numbers of deaths and/or injuries occurring. While each statistic provides a meaningful information, an integrate information of accidents is also very useful. A new statistic "accident size" is adopted in this study, which can be described in terms of the number of deaths and injured persons. From the previous researches, factors such as road geometric conditions, driver characteristics and vehicle types can be related to accidents. However, all those factors interact in complex way so that the interrelationships among the variables are not easily identified. A structural equations model (SEM) is adopted to capture the complex relationships among variables because the model can handle complex relationship among endogenous and exogenous variables simultaneously and furthermore, it can include latent variables in the models. In this study, 704 pedestrian accidents' data has been used, which occurred in Vadodara city of Gujarat, India and estimated the relationships among exogenous factors and traffic accident size. In modeling process, exogenous latent variables such as “road factors”, “vehicle factors” and “time factors” to identify latent relationships to an endogenous variable “accident size” are generated.

Aim of The Study

This study is based on accident analysis using Structural Equation Modeling for pedestrian accidents occurred in five years in Vadodara to understand the parameters that responsible for these accidents. This study explains the role of different factors on road accident size and subsequently transportation planners can take appropriate decisions to reduce the accidents.

Review of Literature

Extensive effort has been made by many researchers in various transportation fields to explain traffic accident occurrence and factors affecting accidents. They attempted to develop different types of model, which can explain severity of accidents and eventually understand and predict the number of accidents. Several selected studies related to ours are summarized among numerous studies, which are accident analysis and SEM. The description of SEM will be presented in next section.

For Hong Kong, the effects of factors influencing on the severity of injury from an accident was examined for factors such as human, vehicle, safety, environment and site. Risk factors associated with each of the vehicle types were identified by means of step wise logistic regression models. For private vehicles, district board, gender of driver, age of vehicle, time of the accident and street light conditions were significant factors for determining the severity of injury (Kelvin and Yau,2004). Milton et al.(2008) proposed a mixed logit model using highway-injury data from Washington State. Findings in their study indicated that volume-related variables such as average daily traffic per lane, average daily truck traffic percentage, number of interchanges per mile and weather effects such as snowfall are best modelled as random-parameters, while roadway characteristics such as the number of horizontal curves, number of grade breaks per mile and pavement friction are best modelled as fixed parameters. Kim et al. (2007) conducted research for the factors contributing to the injury severity of bicyclists in bicycle–motor vehicle accidents using a multinomial logit model. The model predicted the probability of four injury severity outcomes: fatal, incapacitation, non-incapacitation, and possible or no injury. The results showed several factors, which more than double the probability of bicyclist suffering a fatal injury in an accident, all other things being kept constant. Notably, inclement weather, darkness with no streetlights, a.m. peak (06:00a.m. to 09:59a.m.), head-on collision, speeding-involved, vehicle speeds above 48.3 km/h, truck involved, in toxicated driver, bicyclist age 55 or over, and intoxicated bicyclist. Many researches applying the SEMs can be found in transportation fields. These researches try to understand the complex relationships among the variable using SEM.

Hamdar et al. (2008) developed a quantitative intersection aggressiveness propensity index (API). This index was capturing the overall propensity for aggressiveness of driver at signalised intersection. Some important variables obseved in their study were surround traffic and pedestrian, road geometry and design of intersection, signal cycle timings and law enforcement.

The exogenous variables were number of heavy vehicles, number of pedestrians, traffic volume, average queue length, percent grade, number of lanes, number of left turn lanes and so forth. Choo (2007) analyzed telecommunications impacts on travel in a comprehensive system considering demand, supply, costs, and land use, using SEM. The model results suggested that as telecommunications demand increases, travel demand increases, and vice versa. Additionally, transportation infrastructure and land use significantly affect travel demands. In addition, SEM is frequently adopted intravel value and behavior field. Chung and Ahn (2002) developed SEM that presented relationships among socio-demographics, activity participation (i.e., time use), and travel behavior for each day during a week in a developing country. It was tentatively concluded that there were similar relationships between socio-demographics and travel behaviors in developing and developed countries. It was also confirmed that activity patterns were significantly different on weekdays and weekends. Furthermore, during weekdays there were day-to-day variations in the patterns of activity participation and travel behavior. Choi and Chung (2003) adopted multivariate SEM to handle the hierarchical nature of the data and explain complex relationship among socioeconomic factors of individuals and household, activity participation, and travel behavior using Puget Sound Transportation Panel data. Chung and Lee (2002) constructed an SEM to estimate aggregated automobile demand with data from Korea. The results indicated that both the number of driver’s license holders and total road length had a statistically significant effect on automobile demands. In addition, several other determinants of the endogenous variables were found such as average household size, economically active population, personal transportation expenditure, urbanized area, and population density. Lu and Pas (1999) described the development, estimation andinterpretationofamodelrelatingsocio-demographics, activity participation (time use) and travel behavior. Activity participation (time allocated to a number of activity types) and travel behavior were endogenous to the model. They reported the relationships betweenin-homeandout-of- home activity participation and travel behavior.

Structural Equation Model

Structural Equation Modeling is a technique that can model relationship large number of endogenous and exogenous observed variables simultaneously. This technique allows researcher to test various theoretical models that how group of variables define constructs and how they are interrelated. SEM uses ‘latent variables’ which are the unobserved variables and represent unidimensional concepts. The observed variables contain random or systematic measurement errors, but the latent variable is free of these. SEM explains regression, path analysis, factor analysis and canonical correlation analysis as special cases of SEM. SEM facilitates to separate errors in measurement from errors in equations. (Sunyoungahn, 2018)

Elements of SEM

A SEM with latent variables has at most three components as shown in Figure 1: (a) a measurement model for the endogenous variables (Y measurement model), (b) a measurement model for the exogenous variable (X measurement model), and (c) a structural model.

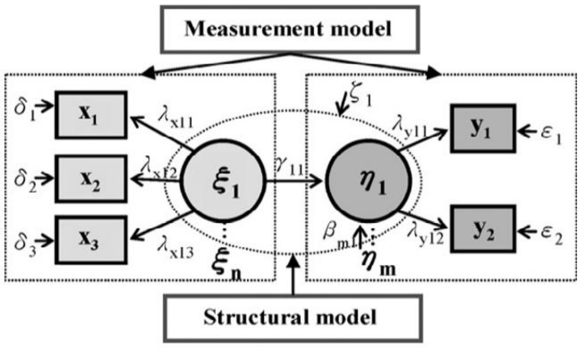
The basic equation of the latent variable model is the following (Bollen, 1989):

$$\eta = B\eta + \Gamma\xi + \zeta \qquad \text{.....(1)}$$

Where:

η (eta) is an (*m* x 1) vector of the endogenous latent variables
ξ (xi) is an (*n* x 1) vector of the exogenous latent variables
ζ (zeta) is an (*m* x 1) vector of random variables
B and Γ are structural coefficient of the model.

Figure 1 an example of SEM



The structural parameters are the elements of the three matrices. B is the matrix (m×m) of direct effects among endogenous latent variables and Γ is the matrix (m×n) of regression effects for exogenous latent variables to endogenous latent variables. Λis linking matrix between the latent and observed variables. The elements of SEM are explained in Table 1.

Table 1 Elements of Structural Equation Model

Measurement model	X	q×1 column vector of observed exogenous variable
	Y	p×1 column vector of observed endogenous variable
	ξ	n×1 column vector of latent exogenous variable
	η	m×1 column vector of latent endogenous variable
	δ	q×1 column vector of measurement error terms for observed variable x
	ε	p×1 column vector of measurement error terms for observed variable y
	Λx	The matrix (q×n) of structural coefficient for latent exogenous variables to their observed indicator variables
	Λy	the matrix (p×m) of structural coefficient for latent endogenous variables to their observed indicator variables
Structural model	Γ	the matrix (m×n) of regression effects for exogenous latent variables to endogenous latent variables
	B	the coefficient matrix (m×m) of direct effects between endogenous latent variables.
	ς	m×1 column vector of the error terms
Covariance matrix	Θ_ε	The covariance matrix (p×p) of ε
	Θ_δ	The covariance matrix (q×q) of δ
	Φ	The covariance matrix (n×n) of ξ
	ψ	The covariance matrix of (m×m) of ξ

The β coefficients (components of B matrix) and the γ coefficients (components of Γ matrix) are magnitudes of expected changes after a unit increases in ηor ξ. Similarly,coefficients (components of Λ matrix) are expected changes of observed variables with respect to a unit change in the latent variable. (Lee et. al - 2008)

Data Description

Growth of road transport in Vadodara city is very fast. There is also considerable increase in vehicle ownership and population in the city. The accident data has been collected from various police station of Vadodara city of the year 2013-2017 with permission of police commissionaire office. This data has been complied and analysed in this chapter.

A total accident data was collected for years 2013-2017. This data included 2854 accidents between all types of vehicles and pedestrian. Further the study of data revealed that, 926 accidents recorded were such in which only one vehicle is engaged, the reason being the accident occurred due to pedestrian collision or vehicle over turned, rolled over or the vehicle made anaccident with road properties or collided with animals. In this field pedestrian accident ratio was dominant with 904 cases vehicle pedestrian accident. Pedestrian involvement in accident is in significant level in the city and it is most vulnerable road users compared to other road users. Because of this reason pedestrian accident model has been developed.

Data encoding of accidentof pedestrian

Coding of data is crucial and important part of data analysis. Before any analysis procedure conducted data should be converted in to proper format so it can be easily applicable to any relevant software and examined into it.

Table 2 shows the coding adopted for accident of pedestrian.

The data used in this study are 704 accident recorded during the year 2013-2017 pedestrian conflicting. Each accident record has rich information such as the divider (whether the road has divider has or not), collision spot, Day or Night (when accident occurred at that time the scenario of time was day or night), Season, weekday, holiday, Collision type, impacting vehicle type, impacting vehicle manoeuvring, impacting vehicle driver gender, pedestrian gender, victim age group, number of injured person, number of deaths.

Table 2 Data Encoding of Pedestrian Accident

No.	Description	Measurement scale
1	Divider	0. No 1.Yes
2	Collision spot	0. Road junction 1. On straight road
3	Impacting Vehicle	0. Bike 1. Auto Rickshaw 2. Car 3. L.C.V. 4. H.C.V.
4	Impacting Vehicle driver gender	0. Man 1. Woman
5	Impacting Vehicle manoeuver	0. Proceeding straight 1. Turning 2. Wrong side
6	Pedestrian gender	0. Man 1. Woman
7	Victim age group	0. Child 1. Minor 2. Adult-1 3. Adult-2 4. Senior citizen
8	Weekday	0. Sunday 1. Monday 2. Tuesday 3. Wednesday 4. Thursday 5. Friday 6. Saturday
9	Day or night	0. Night 1. Day
10	Season	0. Winter 1. Summer 2. Monsoon
11	No. of fatalities	0. No fatalities 1. One fatalities 2. Two or more fatalities
12	No. of injuries	0. No injury 1. One injury 2. Two injury 3. Three or more injury

Conceptual framework of model for pedestrian accident

Table 3Table 3 takes into account divider as a road attribute and displays the proportion of accidents between pedestrian and vehicles in presence and absence of a divider on the carriageway. It was observed that divider had a significant impact on the occurrence of accidents as 73% of accident had occurred in presence of divider. It revealed that a higher proportion of accidents (80%) took place on straight road as compared to that at road junction. This can be attributed to the fact that drivers tend to drive at higher speeds on straight roads in comparison to road junctions as they become cautious at the junctions.

Table 3 Descriptive Statistics of pedestrian accident

Observed variables		Frequency	Percentage	Mean	
				No of Fatalities	**No of Injury**
Divider	No	189	26.85%	0.138	1.053
	Yes	515	73.15%	0.239	0.948
Collision Spot	Road Junction	145	20.60%	0.131	1.090
	On Straight Road	559	79.40%	0.233	0.946
Day or Night	Night	301	42.76%	0.279	0.963
	Day	403	57.24%	0.161	0.985
Season	Winter	245	34.80%	0.220	0.984
	Summer	239	33.95%	0.205	0.971
	Monsoon	220	31.25%	0.209	0.973
Weekday	Sunday	106	15.06%	0.198	1.000
	Monday	91	12.93%	0.242	0.923
	Tuesday	108	15.34%	0.194	0.926
	Wednesday	91	12.93%	0.165	1.077
	Thursday	101	14.35%	0.277	0.911
	Friday	106	15.06%	0.189	1.019
	Saturday	101	14.35%	0.218	0.980

Holiday	No	593	84.23%	0.223	0.963
	Yes	111	15.77%	0.153	1.045
Impacting vehicle type	Bike	329	46.73%	0.106	1.131
	Auto Rickshaw	70	9.94%	0.043	1.071
	Car	170	24.15%	0.241	0.929
	LCV	49	6.96%	0.592	0.490
	HCV	86	12.22%	0.477	0.674
Impacting vehicle Manoeuvre	Proceeding Straight	605	85.94%	0.175	1.018
	Turning	40	5.68%	0.200	1.050
	Wrong Side	59	8.38%	0.593	0.492
Impacting vehicle driver Gender	Man	680	96.59%	0.215	0.963
	Woman	24	3.41%	0.125	1.333
Pedestrian Gender	Man	517	73.44%	0.242	0.926
	Woman	187	26.56%	0.128	1.112
Victim Group	Child	26	3.69%	0.154	0.885
	Minor	52	7.39%	0.096	1.096
	Adult1	159	22.59%	0.170	1.094
	Adult2	335	47.59%	0.260	0.910
	Senior Citizen	132	18.75%	0.197	0.970

It was observed that the proportion of accidents occurring during night time was significantly higher as compared to the day time. Various factors that were found supporting this observation were the night vision of the drivers and pedestrians, poor lighting condition of the vehicle and insufficient street lighting. No significant change was observed in accident size with the variation in seasons similar trend was observed for the effect of weekdays on the accident size. The proportion of accidents were higher (84%) on weekdays as compared to holidays (15%). The reason being the trip purpose on the different days. On weekdays people have to travel for the purpose of work while on holidays, they may or may not travel or travel just for refreshment purpose. Thus, this behaviour makes the proportion of accidents higher on weekdays as compared to holidays. In conjunction to this, holidays are lesser in number with respect to weekdays so, the data is also less.

The accidents involving two-wheeler (2W) were higher as compared to others as the traffic is highly dominated by the two wheelers. Accidents caused by straight moving vehicles were more in proportion as the speeds are higher on straight roads the victims of the drivers in pedestrian driver accident were dominated by males. This was due to the fact that in a country like India males prefer to commute more as compared to females and the later ones are highly dependent on the former for the purpose of making trips. Conversely, the pedestrians affected group by accidents was dominated by females and this can be attributed to the above mentioned reason. As it is clearly observed that adults were vulnerable to accidents as they tend to travel more with respect to other age groups.

Development of SEM

The final model specification is derived using a two-stage development process. At the first stage, factor analysis has been conducted to classify observed variables into several groups. Factor analysis is often used to analyse the correlations among several variables in order to estimate and to describe the number of fundamental dimensions that underlie the observed data. Those fundamental dimensions (factors) can be latent variables in SEM. At the second stage, we estimate the correlations matrix of observed variables and finally develop a SEM having the best-fit statistic. (Lee et. al, 2008)

Factor analysis

Factor analysis is performed on 13 X observed variables, based on the result of which exogenous latent variables are determined. The results of the factor analysis for pedestrian accident with orthogonally rotated are shown in Table 4, which are the correlations between each variable (rows) and each factor (columns). Loadings nearby 0.6 are usually considered 'high' and those below 0.4 are 'low.' The relationship of each variable to the underlying factors expressed by the so-called factor loading.For example, the first factor can be called 'road factor' because it is seems like divider presence and collision spot load highly on it. The second factor can be called 'vehicle factor' because Impacting vehicle and impacting vehicle manoeuvring have high loadings for the factor and also we put pedestrian gender, impacting vehicle driver gender and victim age group in that because it is most suitable in that factor.

Table 4 Rotated Component Matrix Of Pedestrian Accident

No.	Observed variables	Component					
		1	2	3	4	5	6
1	Divider	.208	-.020	.316	.707	-.021	.166
2	Collision spot	-.202	-.017	-.185	.769	-.007	-.198
3	Day night	.110	-.189	-.283	-.006	.584	.336
4	season	.099	.187	-.578	.166	-.081	.308
5	weekday	-.136	-.785	.006	.019	-.177	.040
6	holiday	-.154	.713	-.032	-.010	-.176	.043
7	Impacting vehicle type	.719	-.062	-.144	.077	.073	-.141
8	Impacting vehicle manoeuvre	.735	.041	.134	-.096	-.150	.011
9	Impacting vehicle driver gender	-.146	.002	.053	-.053	.000	.812
10	Pedestrian gender	-.156	.106	.197	-.023	.795	-.154
11	Victim age group	.061	.075	.735	.162	-.012	.227

Finally, three factors are used with exogenous latent variables in the model. Ten observed variables (8 X observed variables and two Y observed variables) into four latent variables (three exogenous and one endogenous variables) for SEM are classified based on the result of factor analysis. Exogenous latent variables are factor1 (road factor), factor 2 (time factor) and factor 3 (vehicle factor) Endogenous latent variable is “accident size factor”.

Abbreviations of parameters

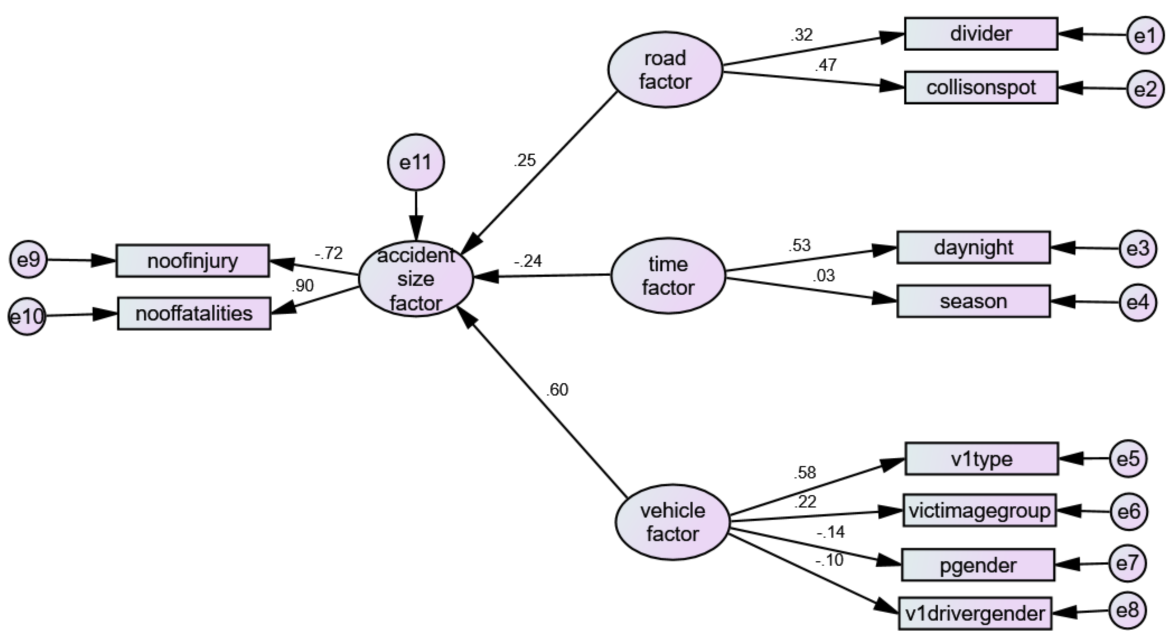
The following Table 5 explains the abbreviations used in the model.

Table 5 Abbreviations of Variables

No.	Abbreviations	Full form
1	Divider	Divider
2	Collisionspot	Collision spot
3	daynight	Day night
4	season	season
5	V1type	Impacting vehicle type
6	V1drivergender	Impacting vehicle driver gender
7	Victimagegroup	Victim age group
8	pgender	Pedestrian gender
9	noofinjury	No. of injury
10	nooffatalities	No. of fatality

Path diagram model for pedestrian accident

Figure 2 Concept model for Pedestrian accident



In our case ML (Maximum likelihood) estimation method is employed. In above figure the regression weights are all standardized regression weights are given.

In anaccident between vehicle and pedestrian, the injuries due to M2W, car and 3W dominated attributing to regression weights calculated in the model. In conjunction to this, from the model it was inferred that fatalities among the victims dominated due to LCV and HCV. The proportion of female was observed to be dominant in the victims affected by accidents. Hence, it was deemed that vehicular factor had a significant influence on the accident size. Inthe model of pedestrian vehicular accident, the vehicular factor had a significant effect on the accident size, as the regression weights had the highest values for the same. The fatalities caused were found higher in the male pedestrians and drivers, whereas injuries dominated for the female pedestrians and drivers. Females were less in the victim group and hence tend to decrease accident size. Under the same factor highest rate of fatalities were found among adults-2 between 30-60 years of age, where injuries were found dominant for minor and adults-1 between 19-30 years of age. The adults of group-2 were found more vulnerable to accidents.

Road factor was found the 2nd most influencing factor on accident size. The presence of divider as a road factor had a contributing effect on the safety of drivers and pedestrians and was responsible for fatal accidents. Whereas, the accidents at road junctions were high but injuries were more among the victims.

Usually time factor, i.e. day or night should have a significant effect on the accident size. Contradictorily, in the model developed the time factor was found to have negative regression weight depicting that it decrease the accident size. Thus, this point forms to be a limitation of the developed model.

In addition to above findings, correlation between fatalities and injuries was evaluated viz. how much proportion of change was observed in injuries when there was a unit change in fatalities. A combined effect of these two variables on accident size was then evaluated. From Table 6 the goodness of fit is quite satisfactory, absolute fit indices determine how well a certain model fits the sample data and allow model with superior fit to be chosen. (Byrne, 2016)

Table 6 Indices of goodness of fit (pedestrian and vehicle accident)

No.	Description	Observed Value	Permissible Value
1	Chi-Square/Degree of freedom	2.851	<=3.00
2	Goodness of fit (GFI)	0.976	>0.90
3	Adjusted Goodness of fit (AGFI)	0.959	>0.90
4	Comparative fit index (CFI)	0.895	>0.90
5	Root mean square residual (RMR)	0.037	<0.10
6	Root mean square Error (RMSEA)	0.051	<0.06 or <0.08

Conclusion

In this research, we postulated that road factors, vehicle factors and time factors are exogenous latent variables and accident size factor is an endogenous latent variable for SEM to analyse traffic accidents size. The observed variables for latent variables are divider, collision spot, day or night, seasons, impacting vehicle type, pedestrian gender, impacting vehicle driver gender, victim age group. Using factor analysis, the 8 variables are grouped into four latent variables (three exogenous and one endogenous variables) for SEM.

The SEM illustrates positive or negative effects of each variable on the accident size. According to the SEM model, the total effect of vehicle factors on accident size is 0.60, so that accident size tends to increase when vehicle factors have higher values. Vehicle factors increase in case of proportion of 2W, car are increases in impacting vehicle type. The estimated coefficient of road factors is a positive value 0.25. This result indicates that road junction and undivided road are tends to decreases accident size. In case of time factors, the estimated coefficient is -0.24, which means that day or night and seasons are tends to decrease accident size.

The estimated coefficients are all standardized solutions, so we can conclude that the major factors influencing on the accident size is vehicle factor. Among three exogenous latent variables (road, vehicle and time factors), the effect of vehicle factor on accident size is highest. In order to decrease the traffic accident size handling the road factor is more effective than handling vehicle and time factors. It can be a positive result to traffic engineers because as they can handle 'road factors', they hardly manage 'vehicle and time factors'. The findings in this research offer information about the relationships between accident size and various factors and they can contribute to reduce traffic accident size. Although there are countless factors having relation to "accident size", obtainable information from fields is very limited. Hence, some aspects may not be properly described and explained by models.

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